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INVESTIGATION ON TAGUCHI BASED NEURAL NETWORK FOR PREDICTING SPECIFIC FUEL CONSUMPTION FOR CI ENGINE FUELED WITH VARIOUS COMPOSITIONS OF PLASTIC PYROLYSIS OIL

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Abstract
Artificial neural networks have been used to overcome obstacles seen in the fields, including healthcare, business, and industry. One significant shortcoming of ANNs is the need for a systematic method to model design. The majority of the literature suggests a time-consuming trial-and-error technique for parameter setting. The amount of momentum, neurons, transfer function, training and learning rate technique all influence the ANN model's accuracy. We use a design of the experimental technique of Taguchi in this research to find the best parameters set for an ANN trained with feed-forward back-propagation. To show the approach's implementation, we give a case study of a specific fuel consumption prediction model for a compression ignition engine. The optimal ANN parameter values are calculated based on the performance statistics after training the network. Compared to random parameter values, the ANN performs better when the Taguchi technique is used to optimize the parameters.
Keyword: Taguchi method, Model selection, neural network optimization, artificial neural network, ANN parameters.

Introduction
Compression ignition (CI) engines have dominated as a source of mechanical power, imparting their important and useful effect in many sectors such as agriculture, industries, and vehicles. Because of the well-known fact that petroleum reservoirs are rapidly depleting, alternative fuel is the fastest-developing fuel replacement in the current environment. Based on the output parameter, Specific fuel consumption can be used to compare different engine types. During the training phase, ANN parameters such as the number of hidden nodes, hidden layers, the transfer functions and the learning rate are established. It is impossible for the ANN model to be successful without these parameters. The approach of trial and error is utilized in order to determine the appropriate values for the ANN parameters. Using the FEA data, Patel and Bhatt created an ANN model. The traditional back-propagation approach has been shown to be the most effective for training the ANN model. The non-linear mapping of output and input parameters is accomplished by the utilization of a multi-layered cognitive network. Production time, money, and resources are all reduced with the Finite Element Analysis - ANN hybrid model.[1].Back-propagation ANN was proposed by chrefler and Lefik for numerically modelling the fundamental behavior of the

physically non-linear object, and their model proved appropriate even for inelastic, complicated, non-linear behavior [2]. Rao and Babu illustrated how ANNs might be used to design beams applied to shear stresses and moments [3]. Gudur and Dixit predicted the position of the velocity field and neutral point using ANN. Data for training is provided using the adamant-plastic FEA algorithm. Their research produced reliable responses that were suitable for use in optimization applications. [4]. ANNGaT, an algorithm for training, was first suggested by Castellani and Rowlands [5]. The weights and topology of the ANN algorithm were developed at the same time. According to their findings, there were no variations in accuracy across ANN topologies' hidden layers. Sholahudin and Han used an advanced ANN model to analyze input parameters. Their findings demonstrate that Taguchi's technique can successfully minimize experimental input parameters. Furthermore, the advanced ANN model accurately estimates instantaneous heating demands with few inputs [6].Patel and Bhatt optimized Eicher 11.10 chassis structure's weight. They employed a technique of Taguchi in conjunction with FEA to reduce tests. This strategy may reduce production costs, resources and time [7]. To optimize the burden of the chassis frame using response surface methodology (RSM) and FEA, Bhatt and Patel created a von Mises stress (VMS) mathematical hybrid model. The VMS regression equation was created utilizing the FEA findings of several chassis frame variations [8]. Patel and Bhatt examined MLR and RSM models to predict the chassis frame's stress. From finding RSM's forecasts shows better results than the MLR model's predictions [9]. Stojanovi 'c et al. explore the tribological behaviour of aluminium hybrid composites using Taguchi's approach. The coefficient of friction and wear rate was predicted using ANN [10].ANN performance is affected by network training settings as well as network architecture parameters. No standard ANN model relevant to all problems has been developed. As a result, the optimal parameter values for each situation must be found experimentally. The statistical Taguchi method was used for parameters influencing the process and their results to predict the relationship. Several writers have used the DOE of the Taguchi path to decide ANN parameters [11–19]. Tortum et al. [11] optimized data transformation, grounding data percentage, layer neuron number, and activation function to increase back-propagation algorithm accuracy. Packianather et al. studied the back-propagation neural network (BPNN) andthe influence of design variables and the performance of veneer wood inspection [13].Roy explained utilising the Taguchi approach to optimise an ANN's design variables. Kuo and Wu created polymer blend predicted models to improve network architecture design flaws using a BPNN and Taguchi's approach. The ANN predicted model's goal was to determine the link between control surface roughness and parameter settings in the coating process of the film[14]. Tannock and Sukthomya employed Taguchi's method to optimize ANN parameters in a multilayer perceptron network trained with back-propagation in the difficult creation process.[15].Laosiritaworn and Chotchaithanakorn investigated the best parameters for an ANN trained to represent data from ferromagnetic materials. They improved the learning pace and momentum. Because [16]. For ANNs, Yum and Jung developed a crucial criteria building method for optimizing parameters including the number of first- and second-layer neurons, momentum, and learning rate. [17]. Madi'c and Radovanovi'c used Taguchi's DOE approach to optimise a trained model of ANN using

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the Levenberg-Marquardt algorithm. The Taguchi-optimised ANN model produced a high prediction accuracy [18].In the wire cut electron discharge machining process for reducing the roughness of the surface, Kazancoglu et al. proposed utilising Taguchi's approach in conjunction with BPNN. Anticipated values were quite close to the trial values [19].The impact of various parameters on the efficiency of wavelet-ANFIS and wavelet-ANN hybrid models were studied by Moosavi et al.. Every model is composed of a number of layers, and Taguchi's method uncovered the most optimal structure prototypes. [20]. Adalarasan and colleagues investigated the drilling properties of 2ndgeneration hybrid composites. Taguchi-based response surface approach using L18 orthogonal array used to optimize the drilling settings [21]. Khoualdia et al. suggested an observing and verification system for gear-bearing combination failure prediction based on an ANN model. Grey-Taguchi method and Taguchi standard orthogonal array were employed as multi-objective optimisation methodologies to discover the optimum ANN model design [22]. Padhi et al. employed fused deposition modelling to create complicated pieces (FDM). Taguchi's approach with ANNassesses the precision of the dimensions of the FDM-fabricated components under different operating situations. The projected values from models agreed with the trial data [23].The end milling procedure for Al2024-T4 work piece material was improved by Sahare et al. The cutting fluid flow rate, feed per tooth, cutting speed, and depth of cut were all input process factors. Material removal rates, the roughness of the Surface, and cutting force were the response parameters. The finding showed ANN paired with Taguchi's approach was appropriate for amendment[24].Taguchi's design of experiments technique was used by Patel and Bhatt to discover the parameter’s optimal set of ANN trained via feed-forward back-propagation. A prediction model of equivalent stress for an automotive chassis shows the approach's implementation. Optimum values of the ANN parameters are calculated based on the performance statistics after the network has been trained. Compared to random parameter values, the ANN performs better when the Taguchi technique optimises the parameters [25].

Materials and Methods

Table 1: Experimental data sets for ANN training [Patel & Bhatt, 2016]

Sr. No	Experimental Run	Factors				Target SFC (kg/kWh)
		Types of fuel	CR	IP (bar)	Load (kg)	
Types of Fuel:- 1 = Diesel, 2 = LDPE PO, 3 = HDPE PO, 4 = PP PO						
Training Data Sets						
1	2	1	15	200	4.12	0.7631
2	3	1	15	220	8.13	0.4781
3	4	1	15	240	12.33	0.4092
4	5	1	16	180	3.88	0.7637
5	7	1	16	220	12.22	0.4414
6	8	1	16	240	0.13	15.9842
7	9	1	17	180	8.1	0.4814

8	11	1	17	220	0.23	8.2872
9	12	1	17	240	4.22	0.7088
10	13	1	18	180	12.25	0.4389
11	14	1	18	200	0.23	8.9635
12	16	1	18	240	8.22	0.4744
13	17	2	15	180	0.23	8.5068
14	18	2	15	200	4.25	0.6188
15	19	2	15	220	8.28	0.4642
16	21	2	16	180	4.22	0.5427
17	23	2	16	220	12.32	0.3997
18	24	2	16	240	0.17	11.7309
19	25	2	17	180	8.23	0.4458
20	26	2	17	200	12.42	0.3926
21	28	2	17	240	4.13	0.6368
22	29	2	18	180	12.33	0.3215
23	30	2	18	200	0.13	13.6036
24	32	2	18	240	8.21	0.4026
25	33	3	15	180	0.12	18.0943
26	35	3	15	220	8.13	0.4409
27	36	3	15	240	12.21	0.3952
28	37	3	16	180	4.23	0.7079
29	38	3	16	200	8.19	0.3935
30	40	3	16	240	0.23	9.3343
31	42	3	17	200	12.31	0.3746
32	43	3	17	220	0.14	14.2211
33	44	3	17	240	4.29	0.6267
34	45	3	18	180	11.73	0.4401
35	47	3	18	220	4.14	0.7291
36	48	3	18	240	8.22	0.4534
37	49	4	15	180	0.23	9.6329
38	50	4	15	200	4.13	0.6572
39	52	4	15	240	12.1	0.3296
40	54	4	16	200	8.12	0.3882
41	55	4	16	220	12.32	0.3167
42	56	4	16	240	0.26	8.5447
43	58	4	17	200	11.92	0.3070
44	59	4	17	220	0.24	8.3119
45	60	4	17	240	4.24	0.6332
46	61	4	18	180	12.11	0.3285
47	63	4	18	220	4.07	0.6896
48	64	4	18	240	8.31	0.3809

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Validation Data Sets						
49	1	1	15	180	0.13	17.4198
50	6	1	16	200	8.23	0.4742
51	10	1	17	200	12.33	0.4206
52	15	1	18	220	4.22	0.7064
53	20	2	15	240	12.23	0.3440
54	22	2	16	200	8.11	0.4124
55	27	2	17	220	0.24	6.7708
56	31	2	18	220	4.33	0.5671
57	34	3	15	200	4.19	0.6044
58	39	3	16	220	12.35	0.3498
59	41	3	17	180	8.29	0.4878
60	46	3	18	200	0.15	14.3220
61	51	4	15	220	8.24	0.4005
62	53	4	16	180	4.23	0.6296
63	57	4	17	180	8.23	0.3843
64	62	4	18	200	0.2	9.9480

2.1 Parameter of ANN for Optimization

With Taguchi's DOE method, ANN optimization for specific fuel consumption output parameters of compression ignition engines is taken in the current work.

2.1.1 Observation Data

An orthogonal array, often known as an orthogonal array (OA), is a specially built table that is utilized in the process of developing a design of the experiment. The utilization of these tables makes it possible to conduct more consistent testing. For the compression ignition engine, 48 parameter value combinations are tested. The specific fuel consumption for each parameter value combination is calculated using a compression ignition engine.ANN has four neurons in its input layer, each of which corresponds to one of four topological characteristics of a compression ignition engine. (load %, injection pressure, fuel types, and compression ratio)and 1 neuron in the output layer related to the particular fuel consumption (SFC).

2.1.2 Parameters for Neural Network

According to the available research, the design control factors that have an effect on ANN's performance may be broken up into two categories.

- First, the hidden layer neurons, the training technique, and the hidden and output layer transfer functions are all used as ANN construction parameters;
- The ANN learning parameters that include learning rate, decrement and increment factors, and momentum are as follows:. A random weight initialization is regarded noise factor. Table 2 shows the design parameters of ANN and their related levels. This design issue comprises seven primary parameters, one of which has two levels while the other six have three.

Considering all potential combinations of the seven factors results in a total of 21 ×36 = 1458 distinct experiment sets.

Table 2: parameter and levels of ANN architectural and training

Parameter	Explanation of Parameter	Level 1	Level 2	Level 3
A	Training Algorithm	trainscg	trainlm	---
B	Transfer function in a hidden layer	*tansig*	*logsig*	*purelin*
C	Factor for Increment	5	10	15
D	Factor for Decrement	0.05	0.1	0.2
E	Learning Rate	0.001	0.01	0.1
F	Momentum, μ	0.1	0.3	0.5
G	No. of neurons in input hidden layer	2	6	10

2.1.3 Designs for Experiments (Taguchi Technique)

It is impracticable to test all of the above combinations. Through the application of Taguchi's OA approach, it is possible to greatly reduce the necessary number of tests. The degree of freedom (DOF) for ANN's seven parameters is 1+ (6×2) =13. Thus, we employ a mixed OA L18 (21 ×36) with 17 DOFs for experimentation, higher than the ANN design parameter's DOFs. As shown in Table 3, our experimental parameter settings are related to every row of the L18 OA.

Table 3: Taguchi's orthogonal array

Exp. No.	A	B	C	D	E	F	G
1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2
3	1	1	3	3	3	3	3
4	1	2	1	1	2	2	3
5	1	2	2	2	3	3	1
6	1	2	3	3	1	1	2
7	1	3	1	2	1	3	2
8	1	3	2	3	2	1	3
9	1	3	3	1	3	2	1
10	2	1	1	3	3	2	2
11	2	1	2	1	1	3	3
12	2	1	3	2	2	1	1
13	2	2	1	2	3	1	3
14	2	2	2	3	1	2	1
15	2	2	3	1	2	3	2
16	2	3	1	3	2	3	1
17	2	3	2	1	3	1	2
18	2	3	3	2	1	2	3

As a result, 18 tests to assess the accuracy of ANN performance [13].Selecting optimal training and design parameters for an ANN model is the primary focus of the Taguchi-based optimization technique. The performance of the ANN is evaluated using the performance index (PI), which is described by Equation 1 [18].

$$PI = R - RMSE \qquad (1)$$

Where R is the correlation coefficient acquired using whole data between the ANN predictions and the experimental results, and Erms is the RMSE obtained using entire data. Because of the larger-the-better problem of PI accuracy, the optimal S/N ratio is described by Eq. 2 [13]:

$$\text{S/N Ratio} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \qquad (2)$$

The values of the S/N ratios and the PI for every experiment are shown in Table 4.

3 Results and Discussion

3.1 Analyses of Results

Figures 1 and 2 show the S/N ratio data and mean data for the various parameters. The optimal parameter configuration, shown as a circle, yields the highest performance index. According to Table 4 and Figure 2, the optimal values for the ANN parameters are A2B2C1D3E3F2G3.. The best model of ANN is trained using the Levenberg-Marquardt (LM) method using 0.001 as the starting learning rate, μ =0.1 for momentum, 0.05 for decrement, and 5 for Increment. The transfer function of tansigis used in a hidden layer, while the transfer function of purelin is used in the output layer. The buried layer has 6 neurons. Table 5 reveals that the hidden layer's transfer function has the biggest effect on the compression ignition engine's anticipated specific fuel consumption, while the learning rate has the least effect. Input layer neuron count, hidden-layer transfer function, deceleration factor, and momentum. The parameters are, in increasing order of importance, the factor for Increment, the Training Algorithm, and the Learning Rate.

3.2 Confirmation Experiment

Taguchi's technique relies heavily on the finalization of the experiment. The confirmation test is unnecessary if the optimum set is already in the OA. However, the optimal design discovered in this experiment is separate from the OA, necessitating a confirmation test. The A2B2C1D3E3F2G3 parameter value combination is used to construct and train the best ANN model and evaluate its performance.

Table 4: Analysis of Taguchi's Technique

Exp. No.	R^2	MSE	R	RMSE	PI= R-RMSE	SNRA1
1	0.9975	0.0016	0.9987	0.0405	0.9582	-0.3709
2	1.0000	0.0000	1.0000	0.0050	0.9950	-0.0433
3	0.9999	0.0001	1.0000	0.0075	0.9925	-0.0655
4	1.0000	0.0000	1.0000	0.0031	0.9969	-0.0266
5	0.9975	0.0016	0.9988	0.0401	0.9586	-0.3670
6	0.9999	0.0001	0.9999	0.0098	0.9901	-0.0865
7	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577
8	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577
9	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577
10	1.0000	0.0000	1.0000	0.0055	0.9945	-0.0478
11	1.0000	0.0000	1.0000	0.0025	0.9975	-0.0219
12	0.9989	0.0008	0.9994	0.0274	0.9720	-0.2464

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13	1.0000	0.0000	1.0000	0.0025	0.9975	-0.0218
14	0.9994	0.0000	0.9997	0.0065	0.9932	-0.0595
15	0.9992	0.0005	0.9996	0.0233	0.9763	-0.2086
16	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577
17	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577
18	0.7435	0.1454	0.8623	0.3813	0.4810	-6.3577

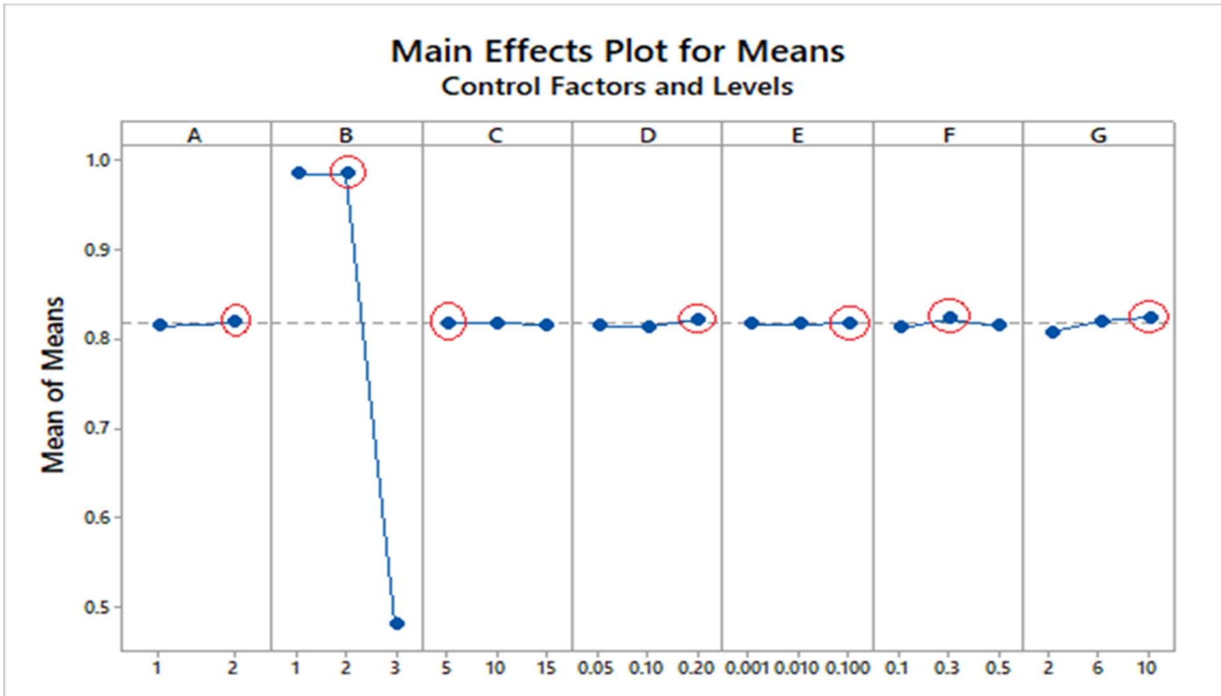

Fig. 1 Performance index mean plot for various parameters.

Figure 3 depicts the LM10TP model's training parameters. Back-propagation of ANN trains with the LM algorithm and has 6 neurons in the hidden layer. Mean Square Error is used to assess performance.The ANN uses the tansig transfer function between the input and hidden layers, and the purelin transfer function between the hidden and output layers. The LM10TP model's training performance (MSE) curve in relation to time is shown in Figure 4.After 1069 epochs, the training was stopped because the performance goal was achievedIt is a useful analytical instrument for evaluating the progression of training.The LM10TP model is retrained for 1069 epochs after initial training, attaining an MSE of $2.6592\times10{-}06$at the training end.Validation datasets that differ from training data previously provided to the network are employed to assess the ANN's prediction accuracy. We employ the following statistical approaches for evaluation: mean squared error (MSE), coefficient of multiple determination (R2) values and root mean squared error (RMSE), Eqs. 3, 4, and 5 are used to calculate these values. The training rates of error and validation are summarized in Table 6.

Table 5: Effect of Different Parameters (Larger is better)

Level	A	B	C	D	E	F	G
1	-2.2259	-0.1326	-2.1971	-2.2239	-2.2090	-2.2401	-2.2932
2	-2.1866	-0.1283	-2.2012	-2.2323	-2.2067	-2.1488	-2.1836
3	*	-6.3577	-2.2204	-2.1624	-2.2029	-2.2297	-2.1419
Delta	0.0393	6.2293	0.0233	0.0699	0.0061	0.0914	0.1513
Rank	5	1	6	4	7	3	2

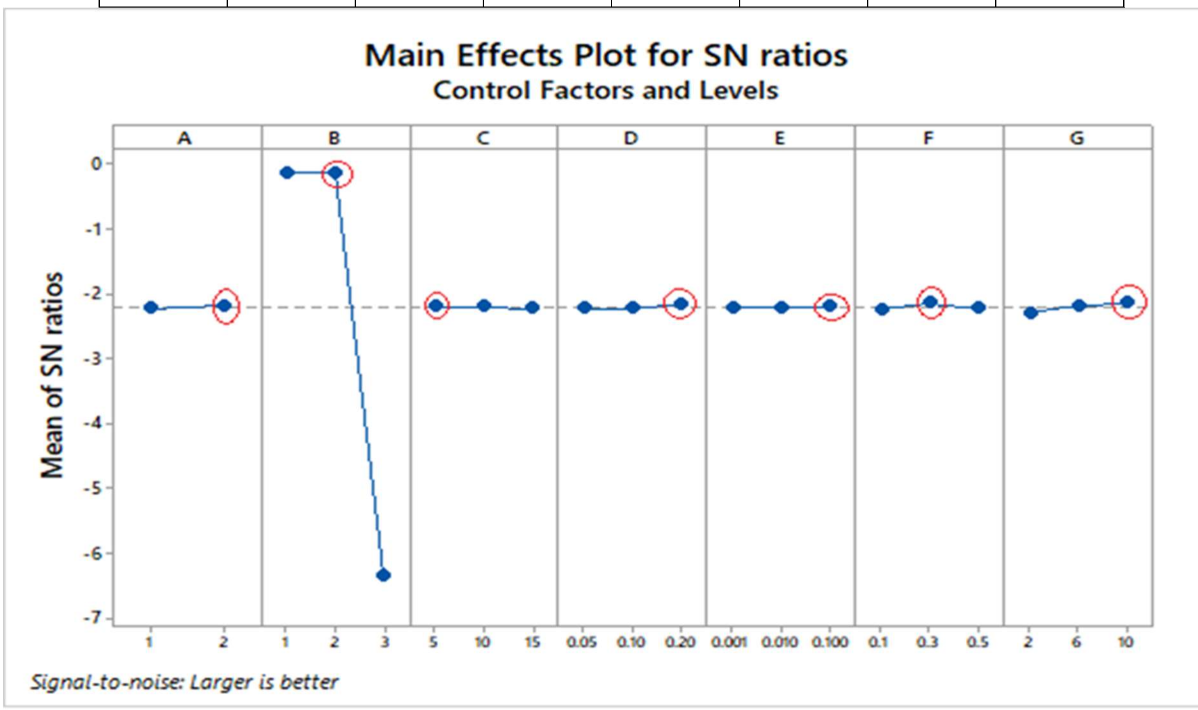

Fig. 2 Performance index S/N ratios for various parameter settings

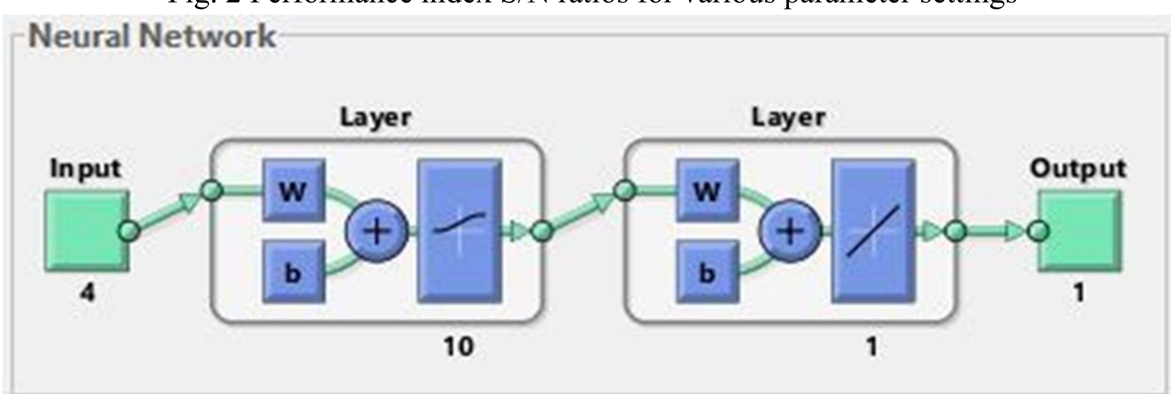

Fig. 3 LM10LP model training

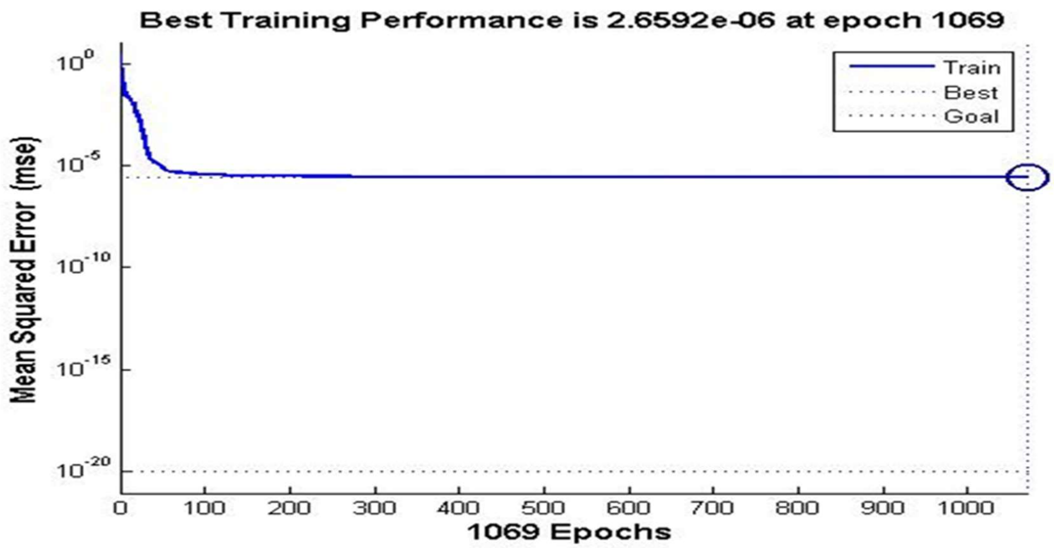

Figure 4: LM10LP model training performance graph

$$\mathrm{MSE} = \left[\frac{1}{n}\sum_{j=1}^{n}\left|a_j - p_j\right|^2\right], \qquad (3)$$

$$\mathrm{RMSE} = \left[\frac{1}{n}\sum_{j=1}^{n}\left|a_j - p_j\right|^2\right]^{1/2}, \qquad (4)$$

$$R^2 = 1 - \left[\frac{\sum_{j=1}^{n}(a_j - p_j)^2}{\sum_{j=1}^{n}(p_j)^2}\right]. \qquad (5)$$

The LM10TP architecture's training data MSE, RMSE, and R2 values are 2.6592×10−06, 0.0031, and 1, respectively. For the LM10TP architecture, the validation data MSE, RMSE, and R2 values are 3.5389×10−05, 0.0059, and 0.9999. Here ANN successfully predicts particular fuel consumption for both the training &validation datasets. No sign of over-fitting due to the same findings for datasets. While an ANN's performance may be judged using errors in the testing and training datasets, studying the network reaction further is typically beneficial. Analysing regression between the network response and the relevant objectives is possible. The LM10TP model linearly closely fits the given target values, as shown in Fig. 5.

Table 6: Errors of ANN data sets

Sr. No	Experimental Run	Factors				Target SFC (kg/kWh)	Predicted SFC (kg/kWh)	Error (kg/kWh)	MSE (kg/kWh)	RMSE (kg/kWh)	R^2
		Types of fuel	CR	IP	Load						
Training Data Sets											
1	2	1	15	200	4.12	0.7631	0.7630	0.0001	2.6592×	0.0016	1
2	3	1	15	220	8.13	0.4781	0.4301	0.0480			
3	4	1	15	240	12.33	0.4092	0.4100	-0.0008			
4	5	1	16	180	3.88	0.7637	0.7384	0.0254			

5	7	1	16	220	12.22	0.4414	0.4412	0.0002
6	8	1	16	240	0.13	15.9842	15.9850	-0.0007
7	9	1	17	180	8.1	0.4814	0.4739	0.0075
8	11	1	17	220	0.23	8.2872	8.2872	-0.0001
9	12	1	17	240	4.22	0.7088	0.7094	-0.0006
10	13	1	18	180	12.25	0.4389	0.4067	0.0322
11	14	1	18	200	0.23	8.9635	8.9622	0.0014
12	16	1	18	240	8.22	0.4744	0.4748	-0.0004
13	17	2	15	180	0.23	8.5068	8.5085	-0.0017
14	18	2	15	200	4.25	0.6188	0.6519	-0.0331
15	19	2	15	220	8.28	0.4642	0.4726	-0.0084
16	21	2	16	180	4.22	0.5427	0.5344	0.0083
17	23	2	16	220	12.32	0.3997	0.4231	-0.0234
18	24	2	16	240	0.17	11.7309	11.7296	0.0013
19	25	2	17	180	8.23	0.4458	0.4763	-0.0305
20	26	2	17	200	12.42	0.3926	0.4242	-0.0316
21	28	2	17	240	4.13	0.6368	0.6341	0.0028
22	29	2	18	180	12.33	0.3215	0.3289	-0.0074
23	30	2	18	200	0.13	13.6036	13.6027	0.0009
24	32	2	18	240	8.21	0.4026	0.4035	-0.0009
25	33	3	15	180	0.12	18.0943	18.0942	0.0001
26	35	3	15	220	8.13	0.4409	0.4264	0.0145
27	36	3	15	240	12.21	0.3952	0.3763	0.0189
28	37	3	16	180	4.23	0.7079	0.7073	0.0006
29	38	3	16	200	8.19	0.3935	0.4193	-0.0258
30	40	3	16	240	0.23	9.3343	9.3338	0.0005
31	42	3	17	200	12.31	0.3746	0.4011	-0.0265
32	43	3	17	220	0.14	14.2211	14.2233	-0.0021
33	44	3	17	240	4.29	0.6267	0.6340	-0.0073
34	45	3	18	180	11.73	0.4401	0.4096	0.0305
35	47	3	18	220	4.14	0.7291	0.7236	0.0055
36	48	3	18	240	8.22	0.4534	0.4545	-0.0011
37	49	4	15	180	0.23	9.6329	9.6334	-0.0005
38	50	4	15	200	4.13	0.6572	0.6589	-0.0016
39	52	4	15	240	12.1	0.3296	0.3268	0.0028
40	54	4	16	200	8.12	0.3882	0.3855	0.0027
41	55	4	16	220	12.32	0.3167	0.3122	0.0045
42	56	4	16	240	0.26	8.5447	8.5437	0.0010
43	58	4	17	200	11.92	0.3070	0.3039	0.0032
44	59	4	17	220	0.24	8.3119	8.3118	0.0000
45	60	4	17	240	4.24	0.6332	0.6341	-0.0009
46	61	4	18	180	12.11	0.3285	0.3416	-0.0131
47	63	4	18	220	4.07	0.6896	0.6907	-0.0011
48	64	4	18	240	8.31	0.3809	0.3764	0.0044

Validation Data Sets											
49	1	1	15	180	0.13	17.4198	17.4521	-0.0323	3.5389×10^{-5}	0.0059	0.9999
50	6	1	16	200	8.23	0.4742	0.4725	0.0016			
51	10	1	17	200	12.33	0.4206	0.4586	-0.0380			
52	15	1	18	220	4.22	0.7064	0.7520	-0.0455			
53	20	2	15	240	12.23	0.3440	0.3684	-0.0244			
54	22	2	16	200	8.11	0.4124	0.4047	0.0077			
55	27	2	17	220	0.24	6.7708	6.8276	-0.0567			
56	31	2	18	220	4.33	0.5671	0.5552	0.0119			
57	34	3	15	200	4.19	0.6044	0.5803	0.0241			
58	39	3	16	220	12.35	0.3498	0.3035	0.0463			
59	41	3	17	180	8.29	0.4878	0.4460	0.0418			
60	46	3	18	200	0.15	14.3220	14.3397	-0.0176			
61	51	4	15	220	8.24	0.4005	0.3637	0.0367			
62	53	4	16	180	4.23	0.6296	0.6962	-0.0667			
63	57	4	17	180	8.23	0.3843	0.2251	0.1592			
64	62	4	18	200	0.2	9.9480	9.9650	-0.0170			

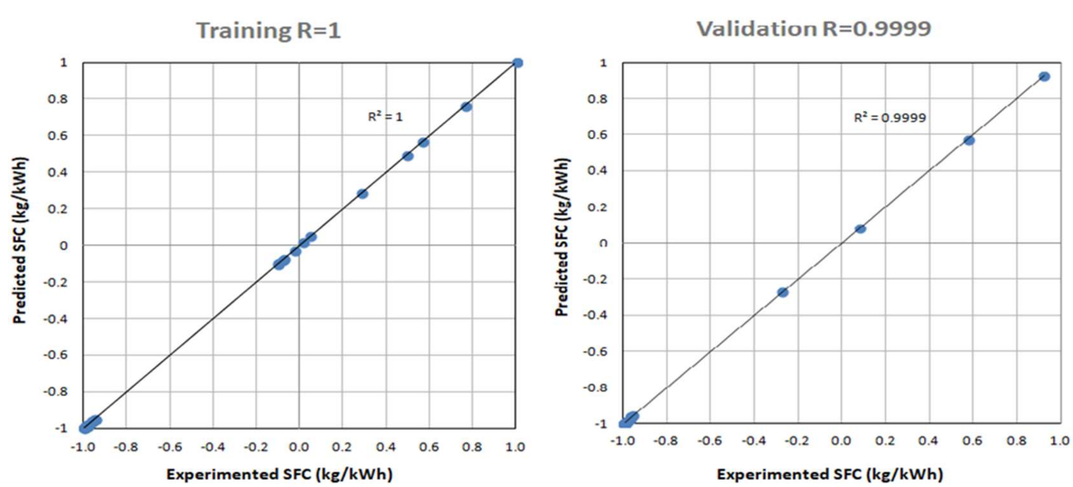

Figure 5: Linear Fitting LM6TP Model in Testing and Training

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It suggests LM10TP model is best fitted for high-precision specific fuel usage. In training and validation, the LM10TP model's anticipated fuel consumption is compared to the actual values, as illustrated in the above figure. Figure 6 demonstrates how well the ANN-predicted outcomes match the actual values.

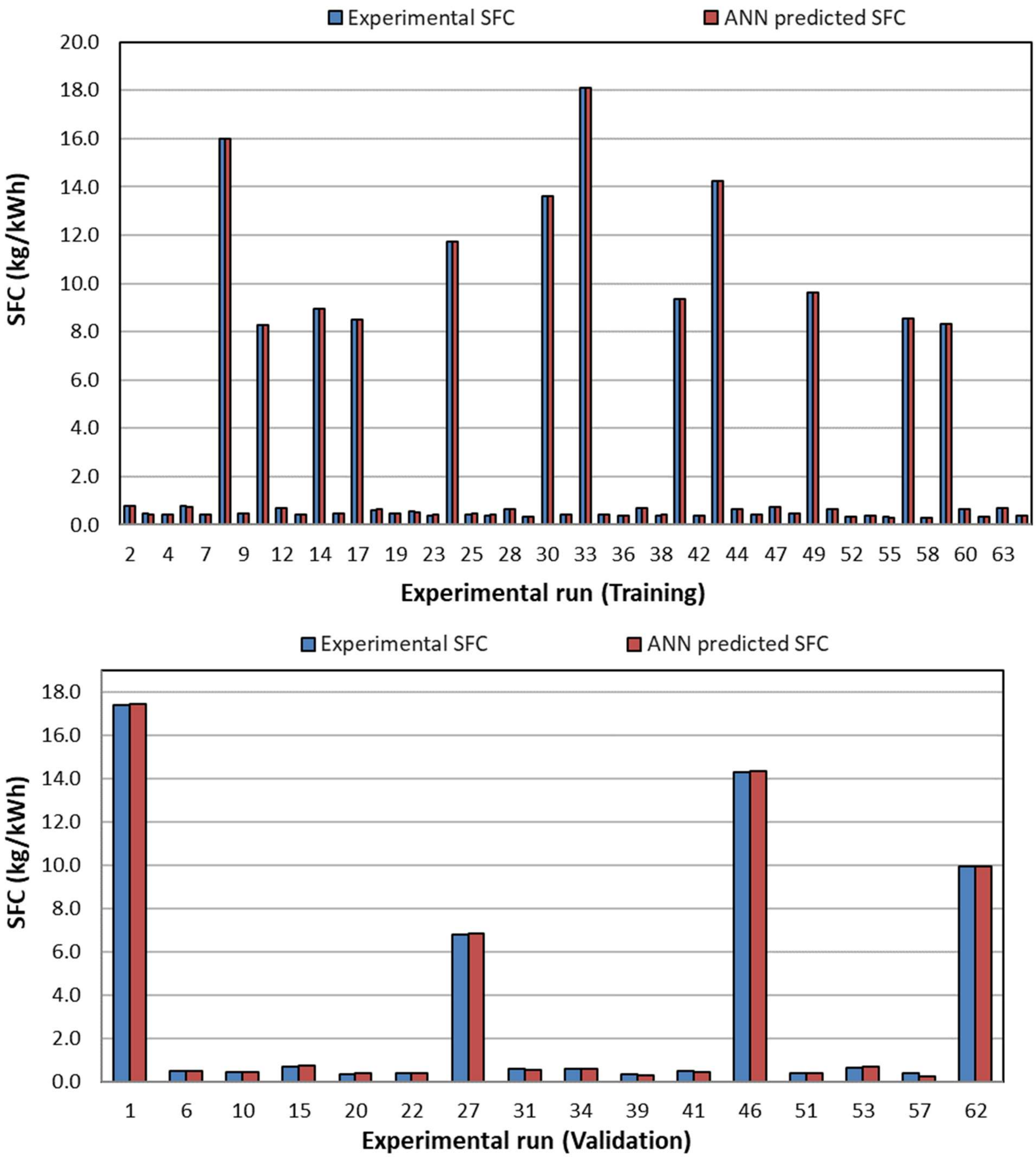

Figure 6: ANN predicted Vs Actual result in Validation and Training

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4. Conclusions

This research aims to apply Taguchi's approach to the parameters development of ANN. The L18 Orthogonal Array was used to organise the seven ANN architectural and training characteristics that were found. Analyses demonstrate that the hidden layer transfer function (B) greatly impacts ANN prediction performance, while the learning rate (E) has the least. This supports the earlier findings of Tortum et al. [11].

1. The optimal ANN model design was discovered to include 10 hidden neurons in the hidden layer. Analysis reveals that increasing the number of neurons in a hidden layer harms ANN performance. This observation confirms Madi'c and Radovanovi'c's [18] conclusion that having numerous neurons in the 1st hidden layer is undesirable when preparing ANNs using the LM approach.

2. The optimum ANN model is an ANN trained with the LM method with 0.001 as the initial learning rate and μ =0.1 as the momentum, 0.05. There are ten hidden neurons that are undetectable to the outside world, the transfer function of purelin at the output layer, and the act as the decrement factor and the increment factor, respectively.

3 In training, the coefficient of determination R2, root mean square error and mean square error values for the LM10TP architecture are 1, 0.0016 and 2.6592×10^{-06}, respectively. For randomly chosen validation datasets, the mean square error, root mean square error, and coefficient of determination R2 for the LM10TP architecture are 0.9999, 0.0059 and 3.5389×10^{-05}, respectively. This shows ANN successfully predicts the particular fuel consumption for the training and validation datasets, with no sign of over-fitting due to the same findings for both datasets.

4. Using a comparably modest and time-saving experiment, Taguchi's technique may be effectively utilized in ANN training and design to generate an optimal ANN model.

5. For the Various ANN applications current research paper’s methodology can be used.

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References:

- Patel, T.M., Bhatt,N.M.: Development of FEA-ANN hybrid model for equivalent stress prediction of automobile structural member. Autom. Control Comput. Sci. 50(5), 293–305 (2016)
- Lefik,M., Schrefler,B.A.: Artificial neural network as an incremental non-linear constitutive model for a finite element code. Comput. Methods Appl. Mech. Eng. 192(28), 3265–3283 (2003)
- Rao, H.S., Babu, B.R.: Hybrid neural networkmodel for the design of beam subjected to bending and shear. Sadhana 32(5), 577–586 (2007)
- Gudur, P.P., Dixit, U.S.: A neural network-assisted finite element analysis of cold flat rolling. Eng. Appl. Artif. Intell. 21(1), 43–52 (2008)

- Castellani, M., Rowlands, H.: Evolutionary artificial neural network design and training forwood veneer classification. Eng. Appl. Artif. Intell. 22(4), 732–741 (2009)
- Sholahudin, S., Han, H.: Simplified dynamic neural network model to predict heating load of a building using Taguchi method. Energy 115, 1672–1678 (2016)
- Patel, T.M., Bhatt, N.M.: FEM based Taguchi method to reduce the automobile structural member weight. GIT-J. Eng. Technol. 8, 1–10 (2015)
- Patel, T.M., Bhatt, N.M.: Development of a mathematical model of VMS for automotive structural member using FEA-RSM hybrid modeling. Procedia Technol. 23, 98–105 (2016)
- Patel, T.M., Bhatt, N.M.: RSM and MLR model for equivalent stress prediction of Eicher 11.10 chassis frame: a comparative study. In: Proceedings of First International Conference on Information and Communication Technology for Intelligent Systems, Springer, Cham. 2, 387–395 (2016)
- Stojanovi´c, B., Vencl, A., Bobi´c, I., et al.: Experimental optimization of the tribological behaviour of Al/SiC/Gr hybrid composites based on Taguchi's method and artificial neural network. J. Braz. Soc. Mech. Sci. Eng. 40(6), 311 (2018)
- Tortum, A., Yayla, N., Çelik, C., et al.: The investigation of model selection criteria in artificial neural networks by the TaguchiN method. Physica A 386(1), 446–468 (2007)
- Packianather, M.S., Drake, P.R., Rowlands, H.: Optimizing the parameters of multilayered feedforward neural networks through Taguchi design of experiments. Qual. Reliab. Eng. Int. 6(6), 461–473 (2000)
- Roy, R.K.: Design of Experiments Using the Taguchi Approach: 16 Steps to Product and Process Improvement. Wiley, Hoboken (2001)
- Kuo, C.F.J., Wu, Y.S.: Application of a Taguchi-based neural network prediction design of the film coating process for polymer blends. Int. J. Adv. Manuf. Technol. 27(5–6), 455–461 (2006)
- Sukthomya, W., Tannock, J.: The optimisation of neural network parameters using Taguchi's design of experiments approach: an application in manufacturing process modelling. Neural Comput. Appl. 14(4), 337–344 (2005)
- Laosiritaworn, W., Chotchaithanakorn, N.: Artificial neural networks parameters optimization design of experiments: an application in materials modeling. Chiang Mai J. Sci. 36(1), 83–91 (2009)
- Jung, J.R., Yum, B.J.: Artificial neural network based approach for dynamic parameter design. Expert Syst. Appl. 38(1), 504–510 (2011)
- Madi´c, M.J., Radovanovi´c, M.R.: Optimal selection of ANN training and architectural parameters using Taguchi method: a case study. FME Trans. 39(2), 79–86 (2011)
- Kazancoglu, Y., Esme, U., Akkurt, A., et al.: Application of a Taguchi-based neural network for forecasting and optimization of the surface roughness in awire-electrical-discharge machining process. Materiali in Tehnologije 46(5), 471–476 (2012)

- Moosavi, V., Vafakhah, M., Shirmohammadi, B., et al.: Optimization of wavelet-ANFIS and wavelet-ANN hybrid models by Taguchi method for groundwater level forecasting. Arab. J. Sci. Eng. 39(3), 1785–1796 (2014)
- Adalarasan, R., Santhanakumar, M., Thileepan, S.: Selection of optimal machining parameters in pulsed CO2 laser cutting of Al6061/Al2O3 composite using Taguchi-based response surface methodology (T-RSM). Int. J. Adv. Manuf. Technol. 93(1–4), 305–317 (2017)
- Khoualdia, T., Hadjadj, A.E., Bouacha, K., et al.: Multi-objective optimization of ANN fault diagnosis model for rotating machinery using grey rational analysis in Taguchi method. Int. J. Adv. Manuf. Technol. 89(9–12), 3009–3020 (2017)
- Padhi, S.K., Sahu, R.K., Mahapatra, S.S., et al.: Optimization of fused deposition modeling process parameters using a fuzzy inference system coupled with Taguchi philosophy. Adv. Manuf. 5(3), 231–242 (2017)
- Sahare, S.B., Untawale, S.P., Chaudhari, S.S., et al.: Optimization of end milling process for Al2024-T4 aluminum by combined Taguchi and artificial neural network process. In: Soft Computing: Theories and Applications, Springer, Singapore, pp. 525–535 (2018)
- Patel, Tushar M., and Nilesh M. Bhatt. "Optimizing neural network parameters using Taguchi’s design of experiments approach: an application for equivalent stress prediction model of automobile chassis." Automotive Innovation 1.4 (2018): 381-389.